A Multi-tier Communication Scheme for Drone-assisted Disaster Recovery Scenarios

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***Abstract*—Disaster scenarios are particularly devastating in urban environments, which are generally very densely populated. Disasters not only endanger the life of people, but also affect the existing communication infrastructure. In fact, such an infrastructure could be completely destroyed or damaged; even when it continues working, it suffers from high access demand to its resources within a short period of time, thereby compromising the efficiency of rescue operations. This work leverages the ubiquitous presence of wireless devices (e.g., smartphones) in urban scenarios to assist search and rescue activities following a disaster. It considers multi-interface wireless devices and drones to collect emergency messages in areas affected by natural disasters. Specifically, it proposes a collaborative data collection protocol that organizes wireless devices in multiple tiers by targeting a fair energy consumption in the whole network, thereby extending the network lifetime. Moreover, it introduces a scheme to control the path of drones so as to collect data in a short time. Simulation results in realistic settings show that the proposed solution balances the energy consumption in the network by means of efficient drone routes, thereby effectively assisting search and rescue operations.**

***Index Terms*—Disaster recovery, multi-tier communication, drone-based data collection, energy-efficiency**

I. Introduction

Natural disasters – such as earthquakes, tsunamis, volcanic eruptions, and flooding – cause substantial damage in terms of both human lives and infrastructure costs, especially in densely populated urban environments. The first 72 hours after a disaster are particularly critical: they are referred to as the *golden relief time* and they are exactly when exhaustive research and rescue activities take place [1, 2]. In particular, communication networks (e.g., cellular base stations) could be completely destroyed or damaged; even when they continue working, they suffer from high access demand to their (limited) resources. This, in turn, exposes both people and rescue teams to the denial of communication services.

Disaster scenarios pose crucial questions regarding the most efficient way to establish communication in terms of time, energy, cost, and practicality. In particular, survivors must be able to send out emergency requests (including location data) and heartbeat-like messages. Systems that rely on smart devices can fully take advantage of their intrinsic heterogeneous and ubiquitous nature [3]: extending the wireless connectivity coverage in areas with missing or damaged infrastructure [4]. Moreover, the multiple interfaces (e.g., Bluetooth, WiFi, and cellular) available on to-date smart devices can be leveraged for energy-efficient communication.

Data dissemination under missing or damaged communication infrastructure has received increasing attention in the last few years [3, 5, 6]. However, most of the related solutions are based on opportunistic device-to-device communications involving a single interface (such as WiFi) [3]. In contrast, [7] leverages multiple wireless interfaces for alert diffusion during disasters. Unfortunately, such a solution assumes a certain level of organization of rescue teams over the affected areas, such that data can be eventually collected directly from the devices, which may incur in a significant delay.

In this respect, UAVs (Unmanned Aerial Vehicles) are particularly suitable as they can quickly and easily cover affected areas [8]. In particular, drones can effectively complement the availability of embedded wireless devices in providing an on-demand communication infrastructure in case of natural disasters [9, 10]. Specifically, smart devices can communicate with aerial base stations, i.e., UAVs that fly over a disaster area with on-board femtocells [11, 12]. However, using drones for disaster recovery poses two key challenges. First, survivors should be reliably discovered as soon as possible. This also means that energy-efficient communication protocols should be in place to extend the time devices owned by survivors can be used for emergency response. Second, the affected area should be covered in the shortest possible time while reaching as many survivors as possible. Unfortunately, these aspects have not received much attention in the literature, which often solely addresses placement and optimization of UAVs for wireless communications in specific areas [13, 14], without considering energy efficiency.

This work specifically addresses these limitations by leveraging the wireless devices already present in urban environment to assist search and rescue activities following a disaster. Specifically, it proposes **a collaborative protocol that organizes wireless devices in multiple tiers to ensure a balanced energy consumption in the whole network**. In doing so, it employs the multiple radio interfaces in off-the-shelf personal mobile devices for energy-efficient operations. Moreover, it introduces **a data collection scheme for drones to visit wireless**

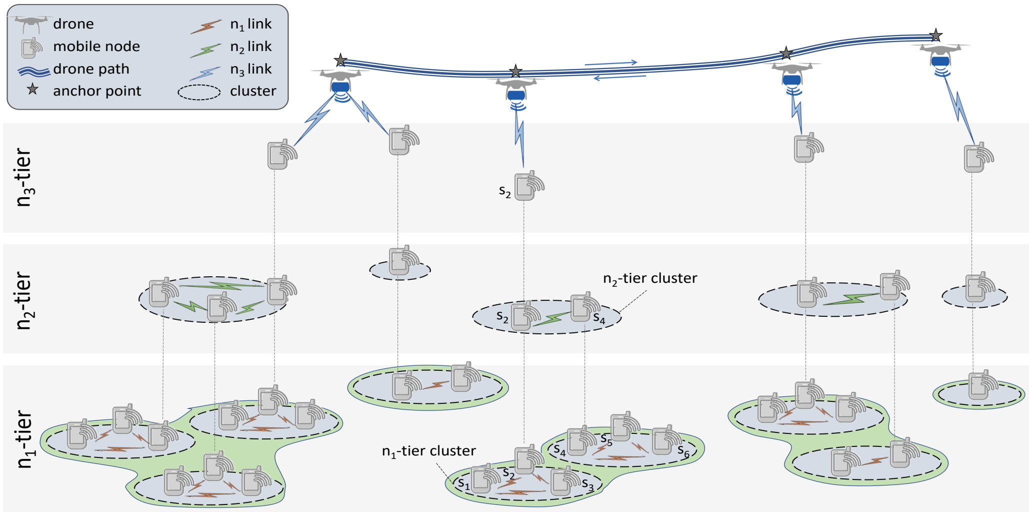


Fig. 1: A three-tier communication architecture: nodes organize themselves into clusters; in each tier, the devices use the same communication technology. The tiers are layered based on the features of these technologies, with the shortest range and the most energy-efficient one at the lowest tier. Cluster heads relay data to the upper tier, while the nodes in the highest tier communicate directly with the drone.

devices and collect their data in a short time. Extensive simulations in realistic settings demonstrate that the proposed solution balances the energy consumption in the network by means of efficient drone routes, thereby effectively assisting search and rescue operations.

II. Background

This section introduces the reference multi-tier architecture, the system model and the key notation used.

A. Reference Architecture

The considered environment consists of mobile devices equipped with multiple network technologies, such as those available in off-the-shelf smartphones (e.g., Bluetooth, WiFi, and cellular). These technologies are characterized by different transmission ranges and energy consumption characteristics [7]. Accordingly, a multiple-tier architecture is created by grouping devices capable of reaching each other directly (i.e., in a single hop) into K clusters, as illustrated in Figure 1. The devices (nodes) in each tier all use the same communication technology and tiers are layered depending on their features: the lowest (highest) tier is the one with the most energy-efficient (energy-hungry) communication technology, but also with the shortest (highest) communication range. Intermediate tiers are characterized by increasing levels of energy efficiency and decreasing transmission ranges. The proposed network structure is not restricted to a specific number of tiers. Figure 1 shows a network composed of three tiers, for instance, corresponding to Bluetooth (n_1), WiFi (n_2) and cellular (n_3) communication technologies. This is also the most realistic option in practice, given currently available smartphones.

One node in each cluster is designated as CH (cluster head). The CH is the node that acts as a bridge between different tiers: it collects data from one tier and relays them to the upper tier. For example, node s_4 in Figure 1 is a CH for the cluster that includes nodes s_5 and s_6 in the n_1 tier. Instead, node s_2 is a CH in two clusters: the one that includes nodes s_1 and s_3 in the n_1 tier, and the one that contains node s_4 in the n_2 tier.

In addition to the mobile devices, the network also includes drones that are sent on-demand to the area of the disaster. In particular, drones are equipped with on-board femto-cells, and provide ad-hoc cellular communication to the nodes in the highest tier [15, 16]. In particular, a drone makes a tour of the network by reaching certain designated locations where it collects data from one or more nodes, depending on the specific path planning algorithm employed (refer to Section III-B for more details). In the previous example, node s_2 is the only one able to communicate with the drone in the n_3 tier among all nodes in the clusters it belongs to.

The adopted architecture supports energy-efficient operations for both the mobile devices and the drone. On the one hand, it allows to preserve the battery power of mobile devices by making them cooperate and elect CHs as intermediate relays responsible for communications up to the highest tier. On the other hand, it simplifies path planning of the drone – hence its energy – by reducing the number of nodes in the highest tier with which the drone communicates directly and exchanges data.

B. System Model

The system includes the set $\mathcal{S} = \{s_1, s_2, \ldots, s_M\}$ of $M = |\mathcal{S}|$ nodes representing survivors at their locations.

The node density is relatively sparse, i.e., nodes might not all be connected; the cluster formation among multiple nodes is not guaranteed and clusters may consist of a single node. Moreover, each node is characterized by an initial available (battery) energy level e_{s_m}. The system also comprises the set $\mathcal{N} = \{n_u, 1 \leq u \leq U\}$ of communication interfaces, where U is the number of available interfaces. Furthermore, the communication interfaces are ordered based on their energy consumption c as $c_{n_1} < c_{n_l} < c_{n_U}$, and transmission range r as $r_{n_1} < r_{n_l} < r_{n_U}$, $\forall l$ such that $1 < l < U$ [17]. Mobile devices are carried by survivors who move slowly if at all. This assumption is justified by the high chance that the survivors are unable to walk fast or run, due to possible injuries and the many obstacles that the natural disaster causes.

The drone collects data from survivors and make them available to SRTs (search and rescue teams) [8, 15]. The drone operates as follows: it plans a path that visits nodes; it then flies over the area according to such a path. Specifically, the drone initially covers all the target area by dividing it into strips and goes over them one by one to discover the nodes and their location [18]. Afterwards, the drone moves with a fixed speed between target locations, where it stops for a certain amount of time to collect data. This can easily be accomplished, for instance, by using a rotary-winged drone. For the sake of simplicity, the following considers a single drone only. The presented solution could be easily extended to multiple drones, for instance, by partitioning the area affected by the disaster into non-overlapping regions.

III. Multi-tier Communication

This section introduces the two phases of the proposed communication scheme for disaster recovery: how to organize node into clusters and how to plan drone routes.

A. Cluster Formation

Cluster formation finds the set of nodes in clusters for each of the tiers and further selects CHs accordingly. CHs bridge communication between different tiers in a multi-tier network architecture, as introduced earlier. Moreover, clusters are periodically updated (e.g., every δt time) so as to balance the energy expenditure in the network. In practice, nodes activate a certain interface to discover their 1-hop neighbors in the corresponding tier. Then, they exchange the list of their neighbors and power budgets to derive their 2-hop neighborhood. In the rest of the article, nodes at a certain tier are assumed to be part of exactly one[1] cluster.

The following presents an optimization problem that derives the clusters in the different tiers and selects CHs to maximize the energy fairness. The problem is shown to be NP-hard. Consequently, a heuristic is devised to collaboratively build clusters based on the local connectivity of the nodes.

1) Optimal multi-tier cluster formation: Optimal cluster formation, i.e., cluster cardinality and CH selection, aims at maximizing balanced energy expenditure among nodes. Such an optimization takes place in the n_u tier, with $1 \leq u < U$, in turns. In fact, CHs of clusters with a high number of member nodes are subject to high energy expenditure. This can also be described as the OMCF (Optimal Multi-tier Cluster Formation) optimization problem below that minimizes the difference between the highest and the lowest energy levels of the nodes in the network (z_{max} and z_{min} respectively), as described in Eq. (1).

$$\min \quad z_{max} - z_{min} \tag{1}$$

$$\text{s.t.} \quad z_{min} \leq \sum_{k \in K} x_{ik}\ (E_i - e_i) + y_{ik}\ e_i \quad \forall i \in S \tag{2}$$

$$\sum_{k \in K} x_{ik}\ (E_i - e_i) + y_{ik}\ e_i \leq z_{max} \quad \forall i \in S \tag{3}$$

$$z_{min},\ z_{max} \geq 0 \tag{4}$$

$$x_{ik} \leq y_{ik} \quad \forall i \in S,\ \forall k \in K \tag{5}$$

$$\begin{gathered} d_{ji}\ y_{jk} \leq r_u\ x_{ik} + D\ (1 - x_{ik}), \\ \forall i, j \in S,\ \forall k \in K,\ \forall u \text{ s.t. } 1 \leq u < U \end{gathered} \tag{6}$$

$$\sum_{i \in S} x_{ik} = 1 \quad \forall k \in K \tag{7}$$

$$y_{ik} \leq \sum_{i \in S} x_{ik} \quad i \in S,\ k \in K \tag{8}$$

$$\sum_{k \in K} y_{ik} = 1 \quad \forall i \in S \tag{9}$$

$$x_{ik},\ y_{ik} \in \{0, 1\} \quad \forall i \in S,\ \forall k \in K \tag{10}$$

In the formulation described by Eqs. (1)–(10), the energy consumption of a node depends on its role, i.e., it consumes e_i energy if node i is member of cluster k, whereas it consumes E_i energy if the node is CH. That is, e_i is the energy spent from a member node to transmit data to a CH, while E_i corresponds to the energy expenditure for transmitting the data of all the cluster members to the next tier or the drone. Specifically, the constraint in Eq. (2) gives a lower bound on the energy expenditure of a node. That is, node i is member ($y_{jk} = 1$) but not head ($x_{ik} = 0$) of cluster k, hence, the energy expenditure amounts to e_i. By contrast, Eq. (3) gives an upper bound on the energy expenditure: node i is head of cluster k and its energy expenditure corresponds to E_i. The bounds z_{min} and z_{max} must be, trivially, non negative values [Eq. (4)]. Moreover, the fact that a node can or cannot be head of a cluster is described in Eq. (5). The condition to be met by nodes to form a cluster is expressed in Eq. (6): any nodes j and i can form a cluster if the distance between them, d_{ji}, is smaller than the transmission range r_u of the interface n_u.

[1]Depending on their connectivity, devices could also be associated with multiple clusters. However, such an option is out of the scope of this article; thus, it is left as a future work.

Algorithm 1 Dynamic CH selection at each node m

Input: nodes location and δt (time-slot)
foreach δt **do**
  $i = 1$; activate interface n_1; ACTIVATED = TRUE;
  while ACTIVATED == TRUE **and** $i < U$ **do**
    discover n_i neighbors and power budgets;
    select node with highest power budget as n_i tier CH (potentially itself);
    if $CH_i = m$ **then** activate n_{i+1} interface; i++;
    else ACTIVATED == FALSE;
  if i == U **then** exchange data with UAV;

If node j is member ($y_{jk} = 1$) and node i head of cluster k ($x_{ik} = 1$), Eq. (6) is satisfied if such nodes are within the transmission range of each other. However, if node i is not head of cluster k, the condition in Eq. (6) is still satisfied for a large enough number D, as a relaxation of the first term in the expression. Furthermore, a cluster can have at most one head [Eq. (7) and Eq. (8)] and a node can belong to at most one cluster [Eq. (9)]. Finally, the binary decision variables in Eq. (10) express the status of a node as a member ($y_{jk} = 1$) or head ($x_{ik} = 1$) of cluster k, and 0 otherwise.

It can be shown that the optimization problem above can be reduced to the maximum-cut problem, which tells if a vertex belongs to the set of vertices yielding the maximum cut (i.e., a partition of the vertices in two disjoint subsets) in a graph [19]. As the maximum-cut problem is NP-complete, the OMCF problem is also NP-complete. A heuristic that obtains an approximate solution to the same problem is described next.

2) Dynamic clustering: The main intuition behind the proposed heuristic is that cluster formation can leverage the local connectivity of nodes at the different tiers; CHs can then be selected to uniformly spread energy consumption between nodes, both over clusters and tiers. CHs need to transmit data over network interface n_u, with $1 < u \leq U$. Hence, they end up consuming energy faster than the other nodes. To maximize clusters lifetime, nodes within the same cluster take turns becoming cluster head for a time interval δt according to their energy level (i.e., the node having the highest energy level will be the CH). The heuristic is described in Algorithm 1.

In the n_1 tier, a CH is responsible to collect the data from the cluster members and switch on the n_2 interface (the n_1 interface is on for all the nodes, by default). In the n_2 tier, new clusters are formed among the CHs of the n_1 tier (see Figure 1). If a node serves as both n_1 and n_2 tier CH, the energy expenditure further increases as it has to collect data from its cluster members in the n_2 tier (which are n_1 tier CHs). Consequently, it switches on the n_3 interface and so on until it activates n_U and transmits such data to an UAV. However, if an n_1 tier CH is a cluster member-only in the n_2 tier, it only has to transmit the n_1 tier data to the CH of the n_2 tier. In fact, there is no need for such a node to switch on the cellular interface. Is it easy to see that the time complexity of Algorithm 1 depends on the network density, particularly, on the number of neighbors of a node. As a consequence, its worst case complexity is $\mathcal{O}(n)$, where n is the number of nodes in the network.

B. Drone-assisted Data Collection

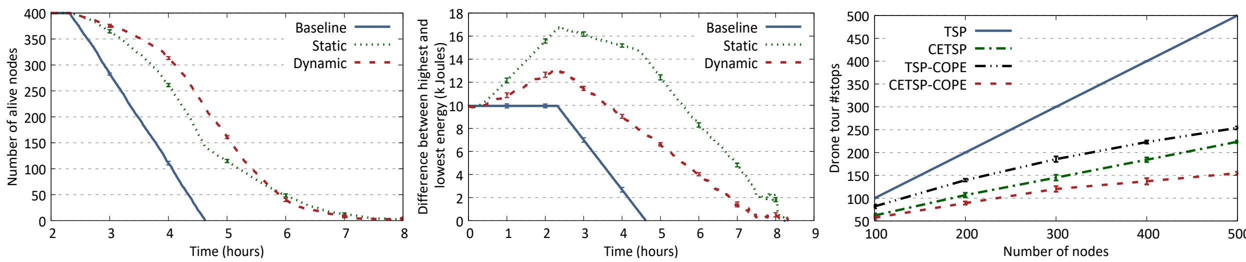
As already mentioned, data collection as well as reporting to rescue teams leverages drones equipped with femtocells as an on-demand communication infrastructure [13]. To fully cover the area affected by the disaster and effectively provide wireless communication capabilities, the drone must visit all the nodes which have switched on the cellular interface (i.e., nodes in the highest tier). The solution proposed in this work operates as follows. Once the nodes are discovered by initially covering the whole target area [18], anchor points are then derived. Anchor points can be either n_U tier nodes or locations from which a drone can reach multiple n_U tier nodes. That is, an anchor point can be anywhere in between the n_U tier nodes it serves. Hence, there is no need for the drone to hover above each n_U tier node – hovering above the (fewer) anchor points suffices to serve all n_U tier nodes. Consequently, the shortest path that visits all these points is then constructed, given anchor points as an input to a path planning algorithm. The drone then follows such a path and collects data.

Several schemes to plan the drone's path are considered to derive the order of visit of the anchor points. Such schemes aim at finding the shortest path that visits all anchor points, with the drone returning to its initial location at the end of a tour (to recharge, for instance). Similar to Section III-A, the design of the path planning algorithms especially focuses on energy consumption – in this case, of the drone. That is, the considered algorithms aim at reducing the tour length of an UAV, hence, the time it takes to fly over a disaster area and collect the data from the nodes. In fact, a short flying time reduces the energy expenditure of the UAV as well.

It is worth noting that cooperation among nodes in the network results in a lower number of nodes in the n_U tier. Consequently, a drone needs to visit fewer anchor points. The last step is to obtain the drone stops that visit all the target locations determined by the multi-tier clustering protocol. This can be accomplished by formulating and solving the Traveling Salesman Problem (TSP) – or its variants, such as the Close-Enough TSP (CETSP) – with the location of n_U tier nodes and anchor points as input [20, 21]. The resulting TSP-COPE and CETSP-COPE schemes are detailed next.

IV. Performance Evaluation

A performance evaluation of the proposed multi-tier data relaying scheme is conducted, with focus on two key aspects: efficiency of relaying data through the tiers in terms of low energy expenditure; and efficiency of



(a) (b) (c)

Fig. 2: (a) Number of alive nodes over time, (b) difference between the highest and the lowest energy values in the network, (c) Number of drone stops for different path planning algorithms as a function of the node density in the network.

deploying an UAV to provide on-demand wireless communication in disaster scenarios in terms of time. Each simulation is replicated ten times and the average values along with the related standard deviations (as error bars) are then reported in the figures.

A. *Cooperative Multi-tier Data Relaying*

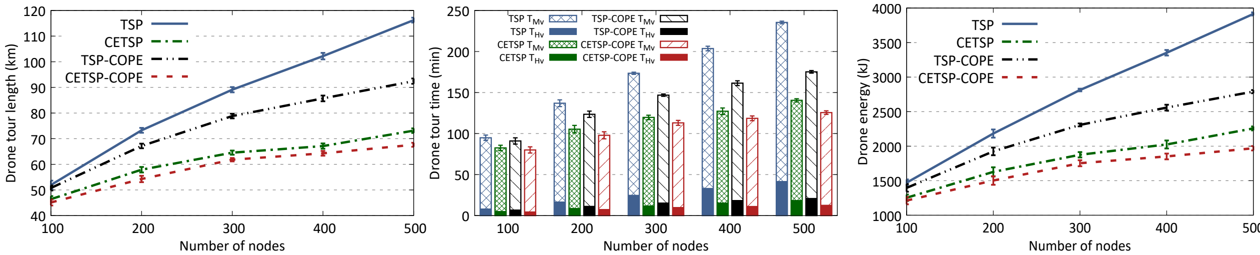
1) Methodology and Setup: The performance of the proposed multi-tier data communication (as described in Algorithm 1) is assessed next. For comparison purposes, two schemes – namely, baseline and static – are also considered.

- *Baseline approach.* It considers every node as a cluster, namely, each node is responsible to switch on all the necessary network interfaces to transmit its own data. Such a scheme leverages no collaboration among nodes.
- *Static approach.* The nodes collaborate among each other to relay their data through the tiers. For such a purpose, nodes in the tier n_u with $u \neq U$ are organized into clusters and only one *responsible* node per cluster relays data to the highest tier until its energy fully depletes. The CHs are selected based on their initial energy: the node with the highest available energy level in the cluster becomes the cluster head. Such a node is then responsible to transmit the data of all the cluster members to the next tier. The status of such a node does not change over time until it dies (i.e., no available energy left), which leads to a new CH.

The disaster scenario consists of a varying number of nodes (survivors) randomly distributed over an urban area of 10 by 5 kilometers. Each survivor is equipped with a mobile device (e.g., smartphone) provided with three network interfaces: Bluetooth, WiFi and cellular, with transmission ranges of 100 m, 200 m, and 500 m correspondingly. Moreover, Bluetooth, WiFi and cellular consume 50 mW, 70 mW and 120 mW respectively [22, 23]. Finally, each node has an initial energy level uniformly distributed in the range of [10 kJ, 20 kJ]. Without loss of generality, CHs are selected once per $\delta t = 15$ minutes [24]. It would not be efficient to choose a very long period of δt as it would lead to a very high energy consumption for CHs. Similarly, a small value of δt requires the nodes to often run Algorithm 1. The following assumes that running Algorithm 1 each δt and switching interfaces on (off) accordingly have a negligible impact on the energy consumption of the devices.

2) Obtained Results: Figure 2(a) shows the number of alive nodes over time. More specifically, 400 nodes randomly distributed in an urban area disseminate their data in accordance with the three schemes: baseline, static, and the dynamic one presented in Section III-A. The baseline scheme, clearly, performs poorly in terms of number of alive nodes over time and energy fairness among them: all the nodes leave the network (due to no energy left) within a relatively short period of time with respect to the golden relief time, and such a trend is almost linear over time. Such is justified by the fact that each node is accountable only for itself, hence, it switches on all the necessary network interfaces. This leads to a large number of nodes depleting their battery at the same time. By contrast, the static scheme outperforms the baseline, leading to a higher number of alive nodes at a given time instant. In fact, the static scheme leads to at least 50 alive nodes more than the baseline scheme and such a gap increases over time. Furthermore, fewer nodes run out of battery at the same time instant. Such a scheme almost doubles the time period within which there is at least one alive node in the network. The proposed dynamic scheme of clustering and CH selection outperforms the baseline and the static schemes. As it introduces unbalanced energy expenditure among nodes, it increases the number of alive nodes at a given time instant compared to the other two schemes. Moreover, most of the nodes run out of battery alone, or in smaller groups. In other words, nodes have comparable energy levels in the network over a longer time. This explains the fact that the static scheme performs slightly better than the dynamic one in the last two hours, approximately in the period from hour 6 to 8.

Figure 2(b) shows the difference between the highest and lowest energy values in the network over time. Similar to Figure 2(a), the cooperative-based schemes (i.e., static and dynamic) outperform the baseline, leading to a lower



(a) (b) (c)

Fig. 3: (a) Tour length, (b) drone hovering and flying time, and (c) energy required by a drone to complete a tour.

energy difference. That is, the energy levels of the nodes present smaller gaps among each other, i.e., the energy burden is more equally distributed across the nodes. The higher initial difference between the energy levels occurs as the nodes with initial low-energy level deplete their batteries soon after data dissemination starts. However, the energy expenditure burden is equally distributed among the remaining nodes in the dynamic case, hence the difference between the highest and lowest energy values is well below that of the static approach. In fact, the static approach puts the energy burden on few nodes that are designated as CHs, thus, the energy gap between the nodes increases. Moreover, the difference between the energy levels in the baseline presents a steep slope because all the nodes in the network are responsible to communicate directly with the drone, thereby switching on all the network interfaces at the same time. Even though the energy consumption is equally distributed, it depletes almost twice as fast as the cooperative-based schemes.

B. Cooperative Data Relaying with UAVs

1) Methodology and Setup: The performance of the proposed TSP and CETSP algorithms with cooperation – namely the TSP-COPE and CETSP-COPE (see Section III-B) – is now assessed and compared to the (*selfish*) TSP and CETSP with no cooperation among nodes. For the sake of clarity, all the four path planning algorithms are summarized below.

- TSP: finds the optimal route that visits each node in the network; there is no cooperation among the nodes to relay data among each other.
- CETSP: determines the minimum number of stops from which the drone can still reach all nodes without having to stop at each of them, and further constructs the shortest path that visits all such stops.
- TSP-COPE: similar to TSP but with node cooperation; the optimal route is calculated based on the location of all nodes in the n_3 tier.
- CETSP-COPE: similar to CETSP but with node cooperation; the optimal route is calculated based on the anchor points obtained from the n_3 tier.

All the four schemes have been implemented as additional modules to the ONE[2] simulator version 1.6.0. The considered scenarios have different network densities, with nodes randomly situated in an urban area. A drone flies over the disaster area with a speed of 10 m/s [25, 26]; it consumes 210 W for hovering and 240 W for moving [26]. The drone stops to collect data from the wireless devices for a time t_c that depends on the cardinality of the cluster C_k and also accounts for the time t_s needed to achieve a full stop. According to preliminary experiments and data sheets of off-the-shelf drones, these values were set to $t_c = 2 \cdot |C_k|$ s and $t_s = 5$ s; the drone then stops for a time $t_a = \min\{t_c, t_s\}$.

2) Obtained Results: Figures 2(c) and 3 show the number of stops, the length, the time and the energy of a drone tour as a function of the number of nodes in the network for the different scenarios. More specifically, Figure 2(c) shows how the number of stops of a drone reduces for the two schemes that offer cooperation, i.e., TSP-COPE and CETSP-COPE. In fact, the number of stops of the TSP scheme with no cooperation increases linearly with the network density; for CETSP-COPE, instead, it increases more slowly. As such density increases, the multi-tier cooperation among nodes becomes more efficient as nodes have more neighbors, hence, they belong to larger clusters. In fact, the number of stops reduces by more than 70% for a density of 500 nodes. Figures 3(a) and 3(b) show how our proposed CETSP-COPE scheme, specifically, outperforms the schemes with no cooperation among the nodes to relay data. This is clearly shown by the fact that the tour length shortens by more than half, and that the drone flying and hovering time reduces by approximately 50% for a high network density. In detail, Fig. 3(a) shows that the difference in the tour length for the four schemes increases with the node density; in fact, the tour length for CETSP-COPE is less than a half that of TSP. Similarly, the flying and hovering times of a drone increase very slowly for the schemes that leverage cooperation, while such values are at least 30% higher for the TSP scheme and high node densities in the network. For instance, the CETSP-COPE drone tour time reduces

[2]https://akeranen.github.io/the-one/

by around 50% compared to the TSP for 500 nodes in the network. However, CETSP outperforms TSP-COPE; this happens as the (higher) cellular transmission range can serve multiple n_3 tier CHs at once, thereby requiring fewer stops than TSP-COPE.

The energy expenditure of a drone depends mostly on the hovering time [27]. Our cooperative schemes (i.e., TSP-COPE and CETSP-COPE) result in less hovering than flying time, even for high network densities. In particular, Figure 3(b) shows that the hovering time (proportional to the number of stops) remains low for all network densities. That is because more clusters with high cardinality are formed as the network density increases, hence, a limited number of n_3 tier nodes relay the data of all the underlaying tier nodes. Moreover, even the flying time is further reduced by our cooperative schemes.

Finally, Figure 3(c) shows the required energy level allowing the drone to complete the tour and to collect data. This energy has been computed by considering the power consumption of the drone when moving and hovering. The results show that CETSP-COPE reduces the energy consumption of the drone since it limits the number of upper tier nodes responsible for data communication between the drone and other nodes. Therefore, in a real environment, CETSP-COPE allows to minimize the number of drones necessary to cover and collect data from a disaster area, and the high cost of the flying cell network [15].

V. Conclusion

This work investigated drone-assisted communication with network self-organization for disaster recovery scenarios. It proposed a dynamic scheme that leverages heterogeneous networks available into off-the-shelf wireless devices such as smartphones. Nodes are organized into multiple tiers and forward emergency messages to a drone flying by. Results obtained through extensive simulations have demonstrated that the proposed scheme is highly beneficial: it allows a longer network lifetime through device cooperation by balancing the energy consumption among nodes; it significantly reduces the duration of drone tours, therefore, the corresponding energy consumption. The proposed solution could be further extended, for instance, by considering fleet of drones flying over the disaster scenario at the same time. In this case, the problem of efficient and fair allocation of certain areas to specific drones would be the main research question. Applying schemes similar to those proposed here in different application scenarios is also a possible extension.

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